Estimation of Time-Varying Wireless Channels and Application to the UMTS W-CDMA FDD Downlink

Massimiliano Lenardi and Dirk T.M. Slock

Institut Eurécom*, 2229 route des Crêtes, B.P. 193, 06904 Sophia Antipolis Cedex, FRANCE

Tel: +33 4 9300 2910/2606 Fax: +33 4 9300 2627 Email:{lenardi,slock}@eurecom.fr

ABSTRACT

In this paper we consider the estimation of mobile channels that are modeled as autoregressive processes with a bandwidth commensurate with the Doppler spread. Pilot based estimation leads to brute FIR channel estimates on a slot by slot basis. These estimates are then refined by Wiener filtering across slots that performs the optimal compromise between temporal decorrelation due to Doppler spread and slot-wise estimation error. We furthermore propose adaptive filtering techniques to implement the optimal filtering. For structured multipath channels, we introduce 2D filtering in which the refined FIR channel estimates are optimally approximated by a multipath model in every slot. The techniques are illustrated with applications from downlink channel estimation in the 3G UMTS W-CDMA FDD system.

1. INTRODUCTION

In the Wideband CDMA (WCDMA) option of the FDD mode of the 3GPP UMTS proposal for cellular wireless communications, the classical single-user receiver used in the forward link is the continuous-time RAKE receiver, which is a channel matched filter (MF), where the (total) channel is the convolution of the spreading sequence, the pulse-shape filter and the multipath propagation channel. The term RAKE refers to a sparse channel impulse response model in which the finite number of specular paths leads to fingers (contributions at various delays) in the channel impulse response. The propagation channel MF is a MF to a sparsified approximation $\hat{h}_{pr}(t)$ for the propagation channel $h_{pr}(t)$.

In this paper we consider a discrete-time RAKE receiver, working at an oversampling rate to satisfy the Nyquist criterion (corresponding to the pulse-shaping bandwidth). The sparse channel representation is done via an approximation strategy in which the convolution of the discrete-time sparse channel model $\hat{h}_k^{pr}$ with the sampled pulse-shape p_k approximates the sampled version of the convolution $p(t) * h_{pr}(t)$ of the true channel and the pulse-shape.

The user codes considered are aperiodic, due to fact that a cell-dependent scrambling gets superposed to the user-dependent spreading; scrambling does not destroy the orthogonality between the intracell users, but it destroys the symbol-interval cyclostationarity of the CDMA signals, making the techniques derived for periodic (short) codes non applicable, e.g. [1].

Previous results in the context of channel estimation in aperiodic-code downlink systems either have computational complexity not suited for MS real-time implementation or they need knowledge of the propagation delays, e.g. [2], [3]. In [4], a multi-rate pilot-aided Least-Squares approach is presented for both the uplink and the downlink, with the possibility of recursive implementation. They assume, however, the use of rectangular pulse-shape filter. They use a Least-Squares-based procedure on the received signal (symbol) samples, which can still lead to high computational complexity for slow-rate users.

In [5] we proposed a sparse channel approximation algorithm, the Recursive Early-Late (REL) algorithm, along the lines of Matching Pursuit techniques, which is again based on pilot-aided Least-Squares, but, due to the whiteness of the training chips, it operates on the FIR estimate of the overall channel, which in general is much smaller than a symbol period.

In this paper, we apply REL to a refined FIR estimate of the overall channel. Pilot-assisted channel estimation operates generally on a slot-by-slot basis, without exploiting the temporal correlation of the channel coefficients of adjacent slots. In [6], an average of the FIR estimate over slots is performed on the basis of a Karhunen-Loéve decomposition of the channel tap autocorrelation function. By applying optimal Wiener filtering across slots, we can provide an alternative approach to refine the brute FIR pilot-based estimates, optimally compromising between temporal decorrelation (Doppler spread) and slot-wise estimation error.

2. AUTOREGRESSIVE CHANNEL MODELS

In the context of the 3G UMTS W-CDMA FDD downlink system, we consider the impulse response (at sampling rate) of the radio channel from the base station BS to a mobile station MS as $h(t,\tau) = \sum_{i=1}^{L} g_i(t) p(\tau - \tau_i(t))$, the convolution of a sparse multipath propagation channel containing L paths with a pulse-shape filter (transmitter filter).

The receiver samples M times per chip the lowpass filtered received signal. Stacking the M samples per chip period in vectors, we get the discrete-time representation of the mobile channel at chip rate $\boldsymbol{h}_l = [h_{1,l} \cdots h_{M,l}]^T$, which represents the vectorized samples of the overall channel, including pulse shape, propagation channel and receiver filter. The overall channel is assumed to have a

*Eurécom's research is partially supported by its industrial partners: Ascom, Swisscom, Thomson-CSF, IBM France, CEGETEL, Motorola, France Télécom, Hitachi Europe and Texas Instruments.

delay spread of N chips, so in matrix notation, we have $\boldsymbol{h}(n) = \boldsymbol{P}\boldsymbol{g}(n)$ where $\boldsymbol{h} = [\boldsymbol{h}_1 \cdots \boldsymbol{h}_N]^T \in \mathcal{C}^{MN\times 1}$, $\boldsymbol{g} = [g_1 \cdots g_L] \in \mathcal{C}^{L\times 1}$ are the complex path amplitudes and the temporal index n is related to the transmission of slot n from the BS to the MS. We consider the channel constant over a slot. If we consider the delays $\tau_i(t)$ constant in a particular environment (we can assume this even in the case of relatively high mobile speed), the pulse-shape convolution matrix $\boldsymbol{P} \in \mathcal{R}^{MN\times L}$ of the delayed pulse shape responses is constant

$$\boldsymbol{P} = \boldsymbol{P}(\tau_1, \cdots, \tau_L) = \begin{bmatrix} \vdots & \vdots & \vdots \\ p(t-\tau_1) & \cdots & p(t-\tau_L) \\ \vdots & \vdots & \vdots \end{bmatrix}$$

where $p(t)$ is the root raised cosine with roll-off 0.22. Even though the notation may suggest a continuous-time pulse shape, the columns of $\boldsymbol{P}$ contain in fact samples of $p(t-\tau)$.

In order to have a simple model for the evolution of the complex path amplitudes over slots and to have low complexity associated optimal filtering algorithms, we can model their variation with an autoregressive (AR) process of order sufficiently high to characterize the Doppler spectrum. If we want to match only the channel bandwidth with the Doppler spread, the resulting first-order AR(1) model is

$$\begin{aligned} &\boldsymbol{g}(n) = \rho\,\boldsymbol{g}(n-1) + \sqrt{1-\rho^2}\Delta\boldsymbol{g}(n) \quad \text{where} \\ &\rho \;=\; \text{channel temporal correlation factor} \\ &\quad = \; 2 - \cos 2\pi f_{3dB} - \sqrt{(2-\cos 2\pi f_{3dB})^2 - 1} \\ &f_{3dB} = \frac{v}{c} f_c\, SP \quad \text{where SP = slot period,} \\ &v, c = \text{mobile,light speed} \quad f_c = \text{carrier frequency} \\ &\sigma^2_{g_k} = \sigma^2_{\Delta g_k} \end{aligned}$$

Therefore, because of $\boldsymbol{P}$ being constant, we have

$$\begin{aligned} \boldsymbol{h}(n) &= \rho\boldsymbol{h}(n-1) + \sqrt{1-\rho^2}\Delta\boldsymbol{h}(n) \\ &= \frac{\sqrt{1-\rho^2}}{1-\rho q^{-1}}\Delta\boldsymbol{h}(n)\,. \end{aligned} \tag{1}$$

q^{-1} denotes the delay operator: $q^{-1}y(n) = y(n-1)$. Variance of $h_k(n)$ (component k of $\boldsymbol{h}(n)$): $\sigma^2_{h_k} = \sigma^2_{\Delta h_k} = \boldsymbol{P}_k\boldsymbol{D}\boldsymbol{P}_k^H$ where $\boldsymbol{P}_k = k^{th}$ line of $\boldsymbol{P}$ and $\boldsymbol{D} =$ diag$\{\sigma^2_{\Delta g_1}, \sigma^2_{\Delta g_2}, \ldots\}$.

3. OPTIMAL WIENER FILTERING OF CHANNEL ESTIMATES

If at the receiver we get/have an estimate of the overall channel, $\hat{\boldsymbol{h}}(n)$, a channel estimation error $\tilde{\boldsymbol{h}}$ has to be considered, $\hat{\boldsymbol{h}}(n) = \boldsymbol{h}(n) + \tilde{\boldsymbol{h}}(n)$, where $\boldsymbol{h}$ and $\tilde{\boldsymbol{h}}$ are mutually uncorrelated, the components of $\tilde{\boldsymbol{h}}$ are uncorrelated and their variance depends on the training symbol power, on the mobile speed and on the SINR, and is independent of position k.

To refine the estimate of the overall channel $\hat{\boldsymbol{h}}(n)$, we propose to process it over slots with the optimal causal Wiener filter. The refined estimate $\hat{\hat{\boldsymbol{h}}}(n)$ is of the form $\hat{\hat{\boldsymbol{h}}}(n) = H(q)\hat{\boldsymbol{h}}(n)$ where $H(q)$ represents the optimal Wiener filter (of unlimited order).

For every component of the channel estimate we can then write

$$\begin{aligned} \hat{\hat{h}}_k(n) &= H_k(q)\hat{h}_k(n) \\ H_k(q) &= \frac{1}{S^+_{\hat{h}_k\hat{h}_k}(q)}\left\{\frac{S_{h_kh_k}(q)}{S^-_{\hat{h}_k\hat{h}_k}(q)}\right\}^+ \end{aligned} \tag{2}$$

where $S_{xx}(q)$ is the power spectral density (PSD) of x, $\{\bullet\}^+$ means "take the causal part of" and $S_{xx}(q) = S^+_{xx}(q)S^-_{xx}(q)$ is the spectral factorisation of $S_{xx}(q)$ in its causal minimum-phase factor and in its anti-causal maximum-phase counterpart. It turns out that, for an AR(1) model for the channel amplitudes given in (1), the PSD of $\hat{h}_k(n)$ is

$$\begin{aligned} S_{\hat{h}_k\hat{h}_k}(q) &= S_{h_kh_k}(q) \;+\sigma^2_{\tilde{h}_k} \\ &= \frac{(1-\rho^2)\,\sigma^2_{h_k}}{(1-\rho q^{-1})(1-\rho q)} \;+\sigma^2_{\tilde{h}_k} \\ &= \sigma^2_{\tilde{h}_k}\frac{a_k\,(1-b_kq^{-1})(1-b_kq)}{(1-\rho q^{-1})(1-\rho q)} \end{aligned}$$

where

$$\begin{aligned} b_k &= \left(\bar{J}_k - \sqrt{(\bar{J}_k)^2 - 4\rho^2}\right)(2\rho)^{-1} \\ a_k = \frac{\rho}{b_k} &= \frac{2\rho^2}{\bar{J}_k - \sqrt{(\bar{J}_k)^2 - 4\rho^2}} \\ \bar{J}_k &= 1 + \rho^2 + (1-\rho^2)\,J_k \\ J_k &= \frac{\sigma^2_{h_k}}{\sigma^2_{\tilde{h}_k}} \quad \text{channel estimation SNR} \end{aligned} \tag{3}$$

Hence

$$\begin{aligned} S^+_{\hat{h}_k\hat{h}_k}(q) &= \sigma_{\tilde{h}_k}\sqrt{a_k}\frac{1-b_kq^{-1}}{1-\rho q^{-1}} \\ S^-_{\hat{h}_k\hat{h}_k}(q) &= \sigma_{\tilde{h}_k}\sqrt{a_k}\frac{1-b_kq}{1-\rho q} \\ \left\{\frac{S_{h_kh_k}(q)}{S^-_{\hat{h}_k\hat{h}_k}}\right\}^+ &= \left\{\frac{\gamma_k q}{1-b_kq} + \frac{\beta_k}{1-\rho q^{-1}}\right\}^+ \\ &= \frac{\beta_k}{1-\rho q^{-1}} \end{aligned} \tag{4}$$

where

$$\begin{aligned} \beta_k &= \frac{(1-\rho^2)\,\sigma^2_{h_k}}{\sigma_{\tilde{h}_k}\sqrt{a_k}\,(1-b_k\rho)} \\ \gamma_k &= \beta_k b_k \end{aligned}$$

Substituting (4) in (2), we have

$$\begin{aligned} H_k(q) &= \frac{\beta_k}{\sigma_{\tilde{h}_k}\sqrt{a_k}\,(1-b_kq^{-1})} \\ \Rightarrow \quad \hat{\hat{h}}_{k,n} &= b_k\;\hat{\hat{h}}_{k,n-1} + \alpha_k\;\hat{h}_{k,n} \end{aligned} \tag{5}$$

where b_k is given in (3) and

$$\alpha_k = \frac{\beta_k}{\sigma_{\tilde{h}_k}\sqrt{a_k}} = \frac{\sigma^2_{h_k}}{\sigma^2_{\tilde{h}_k}}\frac{(1-\rho^2)}{\rho\,(1-b_k\rho)}b_k\,. \tag{6}$$

When there is no time correlation ($\rho = 0$) over slots, we have $b_k = 0$ and $\alpha_k = \frac{\sigma^2_{h_k}}{\sigma^2_{h_k}+\sigma^2_{v_k}}$, that is the filtering weights every component taking into account a priori variance information and channel estimation error.

3.1. Estimation of channel estimation error variance

$\sigma^2_{\tilde{h}} = \sigma^2_{\tilde{h}_k} = \sigma^2_{\hat{h}_k}$ for impulse response samples k at which $h_k(n) \equiv 0$. Hence $\sigma^2_{\tilde{h}}$ can be estimated from $\hat{h}_k$ at delays k where we don't expect the channel to contain any energy. E.g. by overestimating the delay spread, we can use the tail of the channel estimate to obtain an unbiased estimate of $\sigma^2_{\tilde{h}}$ (averaging across slots and across delays k for which $\hat{h}_k \equiv 0$ can be performed.

Alternatively, in order not to increase the length of the channel impulse response to be estimated, we can estimate $\sigma^2_{\tilde{h}}$ from the $\hat{h}_k$ with smallest variance. Consider the variance estimates $\sigma^2_{\hat{h}_k}(n) = \xi\sigma^2_{\hat{h}_k}(n-1) + (1-\xi)|\hat{h}_k(n)|^2$. Note that $\sigma^2_{\tilde{h}}$ is averaged over channel realzations, and hence will only change with changes in channel fading statistics and user powers. Therefore, a long time constant $\frac{1}{1-\xi}$ acn be used here, leading to accurate estimates. Assume that the impulse response h_k contains I samples $\{h_{k_i}, i = 1, \ldots, I\}$ such that $\sigma^2_{h_{k_i}} = 0$ or is sufficiently small (tails of the pulse shape). Let $\{k_i\}$ represent a reordering of the variance estimates $\sigma^2_{\hat{h}_k}(n)$ such that $\sigma^2_{\hat{h}_{k_1}} \leq \sigma^2_{\hat{h}_{k_2}} \leq \cdots \leq \sigma^2_{\hat{h}_{k_{MN}}}$. Then we can estimate $\sigma^2_{\tilde{h}}(n) = \frac{1}{I}\sum_{i=1}^{I}\sigma^2_{\hat{h}_{k_i}}(n)$. This gives in principle a slightly underestimated and hence a biased estimate of $\sigma^2_{\tilde{h}}$. However, this bias will in practice tend to be offset by an energy increase because of leakage from the pulse shape tails.

4. ADAPTIVE WIENER FILTERING (via RLS) OF CHANNEL ESTIMATES

Having in mind the optimal Wiener filtering of (5), we would like to minimize the squared error between the true overall channel delay $h_k(n)$ and its refined estimate $\hat{\hat{h}}_k(n)$, by adapting the two coefficients b_k and α_k to adapt to the Doppler speed of the overall channel taps. We can show that this minimization is equivalent to the minimization of the mean square difference between $\hat{h}_k(n)$ and $\hat{\hat{h}}_k(n)$ (realizable practically) when corrected with a factor dependent only on α_k and $\sigma^2_{\tilde{h}_k}$. Indeed

$$\begin{aligned}&E|\hat{\hat{h}}_k(n) - h_k(n)|^2\\ &= E|b_k\hat{\hat{h}}_k(n-1) + \alpha_k\hat{h}_k(n) - h_k(n)|^2\\ &= E|b_k\hat{\hat{h}}_k(n-1) + (\alpha_k-1)h_k(n)|^2 + \alpha_k^2\sigma^2_{\tilde{h}_k}\end{aligned}$$

and

$$\begin{aligned}&E|\hat{\hat{h}}_k(n) - \hat{h}_k(n)|^2\\ &= E|b_k\hat{\hat{h}}_k(n-1) + (\alpha_k-1)\hat{h}_k(n)|^2\\ &= E|b_k\hat{\hat{h}}_k(n-1) + (\alpha_k-1)h_k(n)|^2 + (\alpha_k-1)^2\sigma^2_{\tilde{h}_k}\end{aligned}$$

Therefore $E|\hat{\hat{h}}_k(n) - \hat{h}_k(n)|^2 + \delta_k$ behaves like $E|\hat{\hat{h}}_k(n) - h_k(n)|^2$ (where $\delta_k = (\alpha_k^2 - (\alpha_k-1)^2)\sigma^2_{\tilde{h}_k} = (2\alpha_k - 1)\sigma^2_{\tilde{h}_k}$).

Introducing temporal averaging over slots, with exponential weighting, we formulate now the RLS adaptation algorithm for the minimization problem stated above. Derivatives with respect to b_k and α_k of (here slot timing is indicated by the second subscript)

$$\sum_{i=0}^{n}\lambda^{n-i}\left(\left|b_k\hat{\hat{h}}_{k,n-i-1} + (\alpha_k-1)\hat{h}_{k,n-i}\right|^2 + (2\alpha_k-1)\sigma^2_{\tilde{h}_k}\right)$$

are forced to zero to give the recursive solution for each component k of the overall channel at each slot n

$$\begin{cases}\boldsymbol{R}_n = \lambda\boldsymbol{R}_{n-1} + Re\left\{\begin{bmatrix}\hat{\hat{h}}_{k,n-1}\\ \hat{h}_{k,n}\end{bmatrix}\begin{bmatrix}\hat{\hat{h}}_{k,n-1}\\ \hat{h}_{k,n}\end{bmatrix}^H\right\}\\ \boldsymbol{P}_n = \lambda\boldsymbol{P}_{n-1} - \begin{bmatrix}0\\ \sigma^2_{\tilde{h}_k}\end{bmatrix}\\ \boldsymbol{\theta}_n = \begin{bmatrix}b_k\\ \alpha_k - 1\end{bmatrix} = \boldsymbol{R}_n^{-1}\boldsymbol{P}_n\end{cases} \quad (7)$$

where *Re*$\{\bullet\}$ means "take real part of". Since the number of coupled parameters is only two, one may as well invert the 2×2 matrix rather than using true RLS. Initialisation of the algorithm requires only R_0 to be different from zero, so we can set it to $R_0 = 10^{-3}\boldsymbol{I}$; furthermore, $\hat{\hat{\boldsymbol{h}}}_{k,0} = \hat{\boldsymbol{h}}_{k,1}$.

5. REL APPROACH

In [5] we proposed the Recursive Early-Late (REL) algorithm. This technique was derived from the basic Early-Late approach, and corresponds here to apply the Matching Pursuit technique to the convolution of the refined FIR estimate of the overall channel $\hat{\hat{h}}_k(n)$ and the pulse-shape matched filter ($p^*_{-k} = p_k$ for the Root Raised Cosine). REL corresponds to maximum likelihood if the noise is Gaussian and white and no other users are present [6].

We assume training chips are sent in every user slot during transmission. Let us define $\boldsymbol{B}_1(n) = \mathsf{B}_1(n)\otimes\boldsymbol{I}_M$ as the block Hankel matrix containing the training chip sequence of user 1 (the user of interest here) in slot n; and $\boldsymbol{Y}$ is the received signal during the training sequence, vectors $\boldsymbol{g}(n) = [g_1(n)\cdots g_L(n)]^T$ and $\boldsymbol{\tau} = [\tau_1\cdots\tau_L]$ are the (complex) path amplitudes and delays ($\tau_i \in [\tau_{min}, \tau_{max}]$, the τ_i are integers here, denoting a delay in units of sampling period). Due to the whiteness of the training chips, the least-squares fitting problem for the sparse channel parameters becomes

$$\begin{aligned}&\arg\min_{\boldsymbol{\tau},\boldsymbol{g}}||\boldsymbol{Y} - \boldsymbol{B}_1(n)\boldsymbol{P}\boldsymbol{g}(n)||^2\\ \approx\ &\arg\min_{\boldsymbol{\tau},\boldsymbol{g}}||\hat{\boldsymbol{h}}(n) - \boldsymbol{P}\boldsymbol{g}(n)||^2\end{aligned} \quad (8)$$

where $\hat{\boldsymbol{h}}(n) = \left(\boldsymbol{B}_1^H(n)\boldsymbol{B}_1(n)\right)^{-1}\boldsymbol{B}_1^H(n)\boldsymbol{Y} \approx \beta^{-1}\boldsymbol{B}_1^H(n)\boldsymbol{Y}$ is the slot-wise FIR channel estimate (used also in [4]) and β represents the training chip sequence energy. To improve the path-wise channel estimate, we replace the slotwise FIR channel estimate $\hat{\boldsymbol{h}}(n)$ in (8) by its filtered version $\hat{\hat{\boldsymbol{h}}}(n)$ to obtain the fitting problem $\arg\min_{\boldsymbol{\tau},\boldsymbol{g}} ||\hat{\hat{\boldsymbol{h}}}(n) - \boldsymbol{P}\boldsymbol{g}(n)||^2$. The sampling rate discrete-time channel impulse response can be written as $h_k = \sum_{i=1}^{L} g_i p_{k-\tau_i}$. When reoptimization is done only for the amplitude of the current iteration, we can formulate the REL algorithm as following (define $f_k^0 = f_k = \hat{\hat{h}}_k * p^*_{-k}$ and $q_k = p_k * p^*_{-k}$):

$$\begin{array}{llll} \text{for} & i = 1, \cdots, L & & \text{or untill } \dfrac{||\boldsymbol{f}_n^i||^2}{||\boldsymbol{f}_n||^2} < \mu \\ & \tau_i & = & \arg\max_k |f_k^{i-1}|^2 \\ & g_i(n) & = & f_{\tau_i}/q_0 \\ & f_k^i & = & f_k - \sum_{l=1}^{i} g_l(n)\, q_{k-\tau_l} \\ & & (= & f_k^{i-1} - g_i(n)\, q_{k-\tau_i}\ ) \\ \text{end} & & & \end{array} \quad (9)$$

where, for example, $\mu = 0.1$.

6. SIMULATIONS

We showed in [7] that the SINR at RAKE output, Γ_R, is

$$\Gamma_R = \frac{E\left\{\sigma_1^2 |\boldsymbol{f}(n)\boldsymbol{h}(n)|^2\right\}}{E\left\{\boldsymbol{f}(n) R_{YY} \boldsymbol{f}^H(n) - \frac{\sigma_{tot}^2}{SF} |\boldsymbol{f}(n)\boldsymbol{h}(n)|^2\right\}}$$

where $\boldsymbol{f}$ is the overall channel MF built with the estimated channel from the REL approach (e.g. in the true channel case, we have $\boldsymbol{f} = \boldsymbol{h}^H(n)$), $\sigma_k^2 = \mathrm{E}\,|a_{k,n}|^2$ (a being the symbols sent by the BS), $\sigma_{tot}^2 = \sum_{k=1}^{K} \sigma_k^2$ and $R_{YY} = \sigma_v^2 I + \frac{\sigma_{tot}^2}{SF} \mathcal{T}(\boldsymbol{h}(n)) \mathcal{T}^H(\boldsymbol{h}(n))$ is the covariance matrix of the received signal, where $\mathcal{T}(\boldsymbol{h}(n))$ is the (block) Toeplitz convolution matrix with the impulse response $\boldsymbol{h}(n)$ and $R_{VV} = \sigma_v^2 I$ is the noise model (which can be extended to a banded block Toeplitz matrix model).

All the active users are considered synchronous and use the same spreading factor SF. The UMTS chip rate is assumed (3.84 Mchips/sec) and an oversampling factor of $M = 2$ is used in the simulations, which show the NMSE (Normalized channel estimation MSE) and the SINR versus the input SNR.

In the figures below, “true ch” refers to a RAKE receiver that has complete knowledge of the channel, “REL FIR” refers to a RAKE that estimates the overall channel via REL on the FIR brute estimate $\hat{h}(n)$, “REL OPT” refers to a RAKE with REL on $\hat{\hat{h}}_{n,k}$ of (5) that uses the optimal b_k of (3) and α_k of (6), “REL EST” refers to a RAKE with REL on $\hat{\hat{h}}_{n,k}$ with filtering parameters b_k and α_k determined by adaptive filtering (7),“REL FIX” refers to a RAKE with REL on the estimate $\hat{\hat{h}}_{n,k}$ where the two coefficients b_k and α_k are fixed (for every component of the overall channel) to ρ and $(1-\rho)$ respectively (the ρ of the AR(1) channel model).

In Fig. 1 to Fig. 4, the environment is UMTS Pedestrian (Ped: 3 km/h, 2 paths, delay spread of about 1 μs, equal average power of the two paths); in Fig. 5 to Fig. 7, the environment is UMTS Vehicular (Veh: 120 km/h, 4 paths, delay spread of 4 chip periods, exponentially decaying average power of the paths); spreading factor is always $SF = 64$ with 5 or 32 users transmitting with equal power and 20% of the slot symbols are considered training symbols; the forgetting factor λ of the RLS algorithm is always 0.99.

We can notice how the SINRs of the various REL implementations are very close to each other, in the SNR range of interest, when few users are active in the system. On the other hand, multi user interference (MUI) degrades channel estimation and hence further degrades SINR, more for non optimal refining as “REL FIR” or “REL FIX”. We can also notice how the NMSE of the “REL EST” channel estimate is always close to the NMSE of the optimal “REL OPT” channel estimate, even in high MUI situation.

7. CONCLUSIONS

We introduced optimal causal Wiener filtering, adapted to the Doppler spread of the channel, to greatly improve the brute FIR pilot-based channel estimation accuracy. The adaptive version of this filtering, via RLS, has a slot as time unit, so its complexity is affordable. Optimal causal Wiener filtering allows optimal compromising between temporal decorrelation and slot-wise estimation error and not only temporal decorrelation like filtering on the basis of a Karhunen-Loéve decomposition of the channel tap autocorrelation function. We proposed the use of the Recursive Early-Late algorithm for approximation of the sparse propagation channel, which exploits the whiteness of the training chips and the pulse-shape filter and exibits smaller complexity with respect to Least-Square techniques that use the all received training chips.

REFERENCES

[1] S. Bensley and B. Aazhang, “Subspace-based channel estimation for code-division multiple access communication systems,” *IEEE Transactions on Communications*, vol. 44, pp. 1009–1020, August 1996.

[2] A. J. Weiss and B. Friedlander, “Channel estimation for DS-CDMA downlink with aperiodic spreading codes,” *IEEE Transactions on Communications*, vol. 47, pp. 1561–1569, October 1999.

[3] Z. Xu and K. Tsatsanis, “Blind channel stimation for long code multiuser cdma systems,” *IEEE Transactions on Signal Processing*, vol. 48, pp. 988–1001, April 2000.

[4] S. Buzzi and H. V. Poor, “Channel estimation and multiuser detection in long-code ds/cdma systems,” *IEEE Journal of Selected Areas in Communications*, vol. 19, pp. 1476–1487, August 2001.

[5] M. Lenardi and D. T. M. Slock, “Channel Estimation for a Discrete-Time RAKE Receiver in a WCDMA Downlink: Algorithms and Repercussions on SINR,” in *Proc. VTC 2001 Fall*, (Atlantic City, NJ), October 2001.

[6] H. Boujemâa and M. Siala, “On a Maximum Likelihood Delay Acquisition Algorithm,” in *Proc. ICC 2001*, (Helsinki, Finland), June 2001.

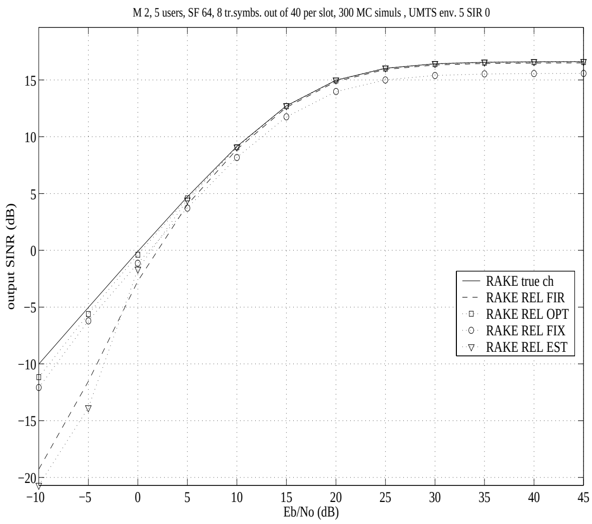

Figure 1: Ped, 3 Km/h, $\lambda 0.99$, 5 users: SINR

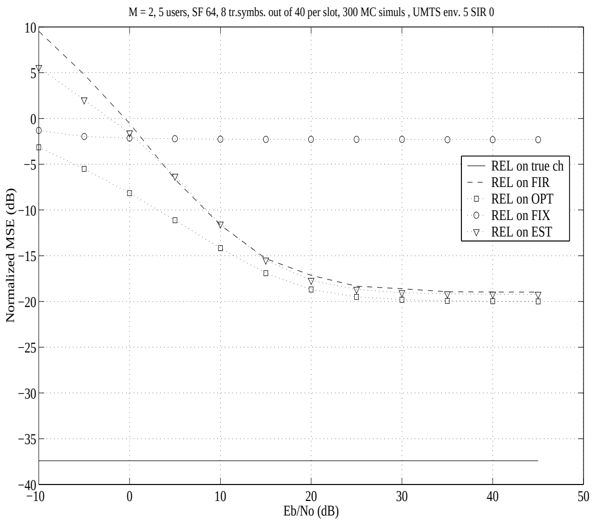

Figure 2: Ped, 3 Km/h, $\lambda 0.99$, 5 users: NMSE

[7] M. Lenardi and D. T. M. Slock, "A RAKE Receiver with Intracell Interference Cancellation for a DS-CDMA Synchronous Downlink with Orthogonal Codes," in *Proc. VTC 2000 Spring*, (Tokyo, Japan), May 2000.

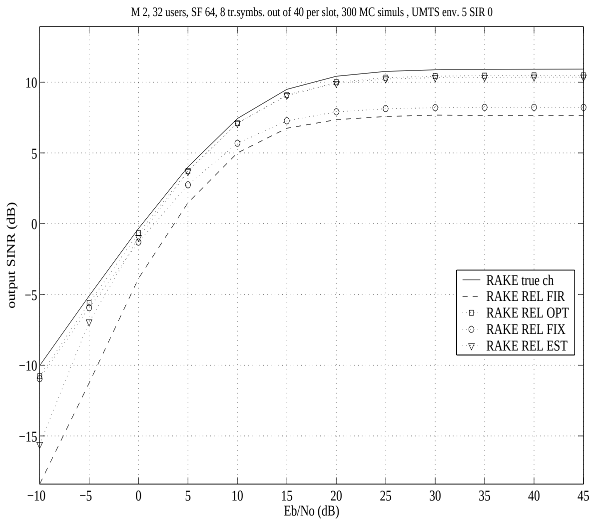

Figure 3: Ped, 3 Km/h, $\lambda 0.99$, 32 users: SINR

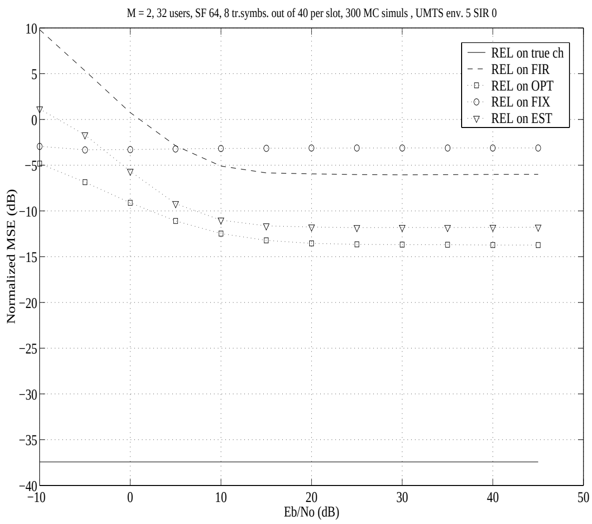

Figure 4: Ped, 3 Km/h, $\lambda 0.99$, 32 users: NMSE

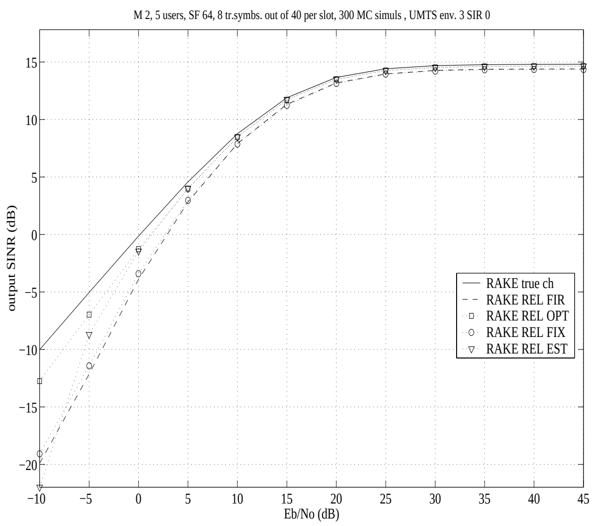

Figure 5: Veh, 120 Km/h, $\lambda 0.99$, 5 users: SINR

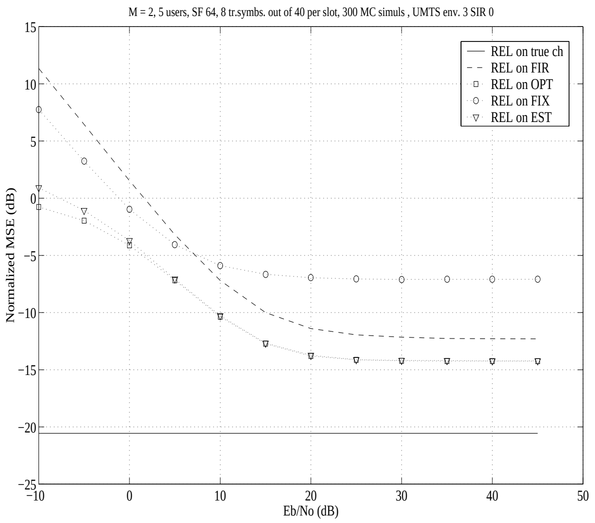

Figure 6: Veh, 120 Km/h, $\lambda 0.99$, 5 users: NMSE

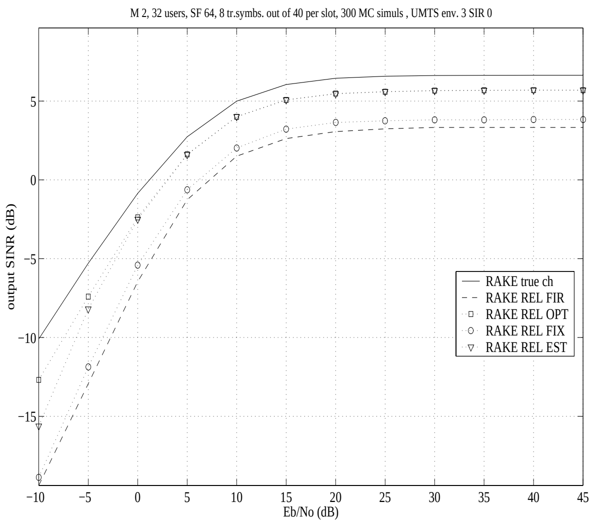

Figure 7: Veh, 120 Km/h, $\lambda 0.99$, 32 users: SINR

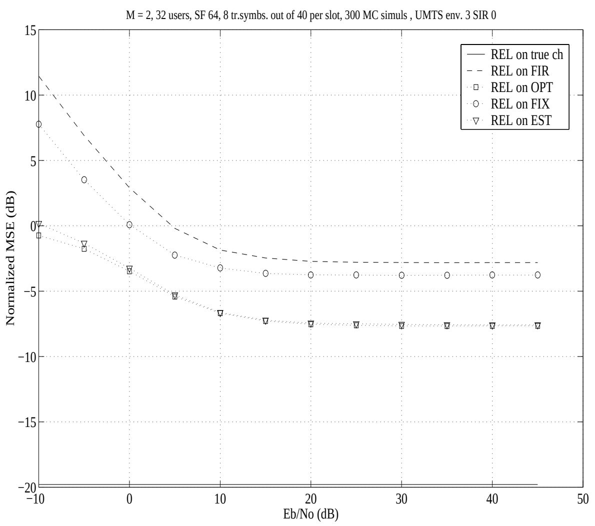

Figure 8: Veh, 120 Km/h, $\lambda 0.99$, 32 users: NMSE